NEONATAL EEG SEIZURE DETECTION USING A TIME-FREQUENCY MATCHED FILTER WITH A REDUCED TEMPLATE SET

John O' Toole, Mostefa Mesbah and Boualem Boashash

Signal Processing Research, Queensland University of Technology,
GPO Box 2434, Brisbane, QLD 4001, Australia.
e-mail: j.otoole@qut.edu.au

ABSTRACT

Electroencephalographic (EEG) recordings are an important diagnostic resource in determining the presence or absence of clinical seizures in neonates. These nonstationary signals require some form of nonstationary analysis to detect seizures in the EEG data. A time-frequency (TF) matched filter has been previously proposed to detect seizures in both adult and newborn EEG. A method which constructs a reference or template set from a feature of EEG seizures, rather than the whole EEG seizure, displayed the most promising results. However this method suffered from an inability to adequately represent patient variability in the template set while simultaneously maintaining a low false detection rate. A new method of the TF matched filter is proposed that halves the template set required by approximating the templates with a more general ambiguity domain function representation. This proposed method is also less sensitive to false detections when a larger reference set is used, as evidenced by the findings on both simulated and real neonatal EEG.

1. INTRODUCTION

The matched filter is a linear filter designed to maximise the Signal to Noise Ratio (SNR) when trying to detect a deterministic signal $s(t)$ embedded in additive noise $n(t)$ [1]. It is assumed that the input to this filter can take two forms,

$$
\begin{aligned}
H_0 &: x(t) = s(t) + n(t) && \text{signal present,} \\
H_1 &: x(t) = n(t) && \text{signal absent.}
\end{aligned}
$$

This filter's aim, therefore, is to attenuate the noise and enhance the signal (if present). At a particular time t_0 the output of the filter $y(t_0)$ can be compared with a pre-selected threshold to determine whether the signal is present or not. For the case when $n(t)$ is white Gaussian noise (WGN), the matched filter is an optimum detector and is equivalent to the correlation of the noisy signal $x(t)$ with the signal $s(t)$ (assumed to be known). This detection method has been extended to the handle nonstationary versions of $s(t)$ by applying the correlation in the TF domain [2] as

$$\eta_{TF} = \int_{\mathbb{R}^2} \rho_x(t,f)\rho_s^*(t,f)\mathrm{d}t\mathrm{d}f$$

where η_{TF} represents the detection statistic and $\rho_s(t,f)$ and $\rho_x(t,f)$ represent the time-frequency distributions (TFD) of the reference signal $s(t)$ and noisy signal $x(t)$ respectively. This detection statistic can be expanded, assuming the TFD adheres to time and frequency covariance properties [3], to incorporate TF shifted versions of the reference $\rho_s(t,f)$ TFD

$$\eta_{TF}(t_0, f_0) = \int_{\mathbb{R}^2} \rho_x(t,f)\rho_s^*(t-t_0, f-f_0)\mathrm{d}t\mathrm{d}f. \quad (1)$$

1.1. EEG Seizure Detection using a TF Matched Filter

Initial attempts at EEG seizure detection for the adult case include a method proposed by Shamsollahi *et al.* [4] to detect EEG seizures in one patient by defining a template TFD from a segment of EEG seizure. The authors concluded that this method worked well when detecting the seizure in the same channel (i.e. estimation of time of arrival of a known signal) but performed poorly when applied to other channels for the patient. Senhadji and Wendling [5] implemented the same detection method on adult EEG but tested the correlation with different types of seizures, again from the same patient. They concluded by stating that the method was unsatisfactory due to the variation of the TF signatures of the different seizures.

Schiff *et al.* [6] identified a component of the adult EEG seizure as a chirp (which will henceforth be denoted as a quasi-linear frequency modulated (quasi-LFM)) signal from intracranial EEG data. From their observations of six patients EEG they associated this feature with EEG seizures and concluded that this quasi-LFM signal is only ever present in EEG seizures. The authors proposed using a TF matched filter with a set of TF seizure templates from spectrogram representations of the EEG containing quasi-LFM signals. No results for the matched filter method were given.

0-7803-9243-4/05/$20.00 ©2005 IEEE

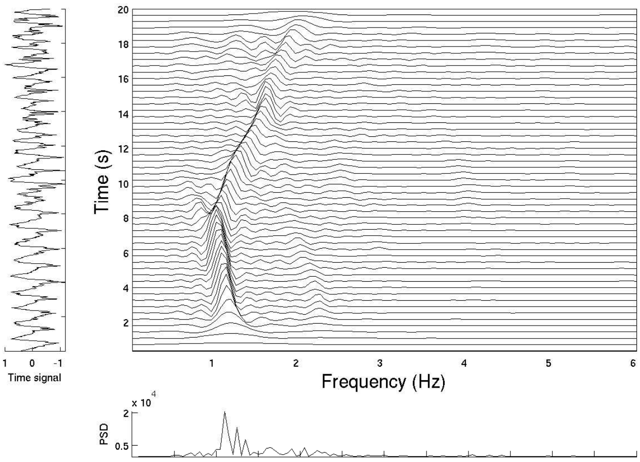

Figure 1: Example of a TFD for an epoch of neonatal EEG seizure data containing a quasi-LFM feature.

Applying the TF matched filter to the neonatal case Boashash and Mesbah [7] proposed building a set of TF seizure templates from an identified feature in the seizure TFD. The feature was extracted through instantaneous frequency (IF) estimation and used to construct a template set based on a piece-wise LFM (PWLFM) signal. The correlation of the PWLFM template to an EEG seizure is best illustrated by example, as can be seen in Fig. 1.

In order to detect the feature rather than trying to find an exact correlation, i.e. where $\eta_{TF}(t_0, f_0)$ is greater than some predefined threshold, another stage is necessary. This involves extracting an IF law from the area mapped by the TF test statistic $\eta_{TF}(t_0, f_0)$ and then making a decision based on the properties of this IF law, i.e. that the IF law represents some form of quasi-LFM signal and is continuous for greater than a threshold time set to 10 seconds. One of the major issues associated with this method is that the greater the number of templates in the template set the greater the number of false detections. Also the quasi-LFM feature characteristics vary from patient to patient which implies that a large template set is needed if the method is to be valid over a range of patients.

A modified method of this TF matched filter will be proposed in the next section that requires a smaller reference set while maintaining the same ability to detect PWLFM signals. This method also displays the property to be less sensitive to false detections with increased template set size.

2. AMBIGUITY DOMAIN TEMPLATE SET CONSTRUCTION

The correlation defined in the test statistic $\eta_{TF}(t_0, f_0)$ expressed in Eq. (1) can be expressed in terms of convolution as

$$\eta_{TF}(t_0, f_0) = \rho_{EEG}(t_0, f_0) \underset{t\ f}{\star\star} \rho^*_{ref}(-t, -f)$$

where $\underset{t\ f}{\star\star}$ represents convolution in the time and frequency domain. Assuming that the TFD $\rho_{ref}(t, f)$ is real and defining $\hat{\rho}_{ref}(t, f) \equiv \rho_{ref}(-t, -f)$ then the test statistic can be expressed in terms of an ambiguity domain function product [3] as

$$\eta_{TF}(t_0, f_0) = \underset{\nu \to t}{\mathcal{F}^{-1}} \left\{ \underset{\tau \to f}{\mathcal{F}} \left\{ A_{EEG}(\nu, \tau) \hat{A}_{ref}(\nu, \tau) \right\} \right\}$$

where $\mathcal{F}$ denotes a Fourier transform and $A_{EEG}(\nu, \tau)$ and $\hat{A}_{ref}(\nu, \tau)$ represents the ambiguity domain function of the EEG epoch and the time/frequency reversed template. The ambiguity function for a signal $z_1(t)$ is defined as

$$A_{z1z1}(\nu, \tau) = \int_{-\infty}^{\infty} z_1(t + \tfrac{\tau}{2}) z_1^*(t - \tfrac{\tau}{2}) \mathrm{e}^{-j2\pi\nu t} \mathrm{d}t$$

which can be termed as $A_{z1}(\nu, \tau)$ for convenience. As an example of $A_{ref}(\nu, \tau)$ consider the case of a two piece PWLFM signal described as $z(t) = z_1(t) + z_2(t)$ where $z_1(t) = \mathrm{rect}(t - T_1/2, T_1)\mathrm{e}^{j2\pi(f_1 + (\alpha_1/2)t^2)}$ and $z_2(t) = \mathrm{rect}(t - (T_1 + T_2/2), T_2)\mathrm{e}^{j2\pi(f_2 + (\alpha_2/2)t^2)}$. The rectangular function rect$(t - t_1, T)$ is defined as 1 in the region $t_1 - T/2 \leq t \leq t_1 + T/2$ and zero elsewhere. The ambiguity function of $z(t)$ consists of both auto and cross terms as $A_z(\nu, \tau) = A_{z1}(\nu, \tau) + A_{z2}(\nu, \tau) + A_{z1z2}(\nu, \tau) + A_{z2z1}(\nu, \tau)$. The auto terms equate to

$$\begin{aligned} A_{z1}(\nu, \tau) &= \mathrm{e}^{-j2\pi\nu T_1/2} \mathrm{e}^{-j2\pi\tau(\alpha_1 T_1/2 - f_1)} \\ &\quad (T_1 - |\tau|)\mathrm{sinc}\{(\nu - \alpha_1\tau)(T_1 - |\tau|)\}\mathrm{rect}(\tau, 2T_1) \\ A_{z2}(\nu, \tau) &= \mathrm{e}^{-j2\pi\nu(T_1 + T_2/2)} \mathrm{e}^{-j2\pi\tau(\alpha_1(T_1 + T_2/2) - f_2)} \\ &\quad (T_2 - |\tau|)\mathrm{sinc}\{(\nu - \alpha_2\tau)(T_2 - |\tau|)\}\mathrm{rect}(\tau, 2T_2) \end{aligned}$$

and the cross terms equate to

$$\begin{aligned} A_{z1z2}(\nu, \tau) &= A_{r1r2}(\nu, \tau) \underset{\nu}{\star} \Big\{ \sqrt{j/(\alpha_1 - \alpha_2)}. \\ &\quad \mathrm{e}^{-j\pi \frac{[(f_1 - f_2) + (\alpha_1 + \alpha_2)/2 - \nu]^2}{(\alpha_1 - \alpha_2)}} \mathrm{e}^{j\pi(\tau^2(\alpha_1 - \alpha_2)/4 + \tau(f_1 + f_2))} \Big\} \end{aligned}$$

where $A_{r1r2}(\nu, \tau)$ represents the cross ambiguity function of the two rectangular functions rect$(t - T_1/2, T_1)$ and rect$(t\text{-}(T_1 + T_2/2), T_1)$. The other cross term $A_{z2z1}(\nu, \tau)$ is obtained by swapping the indices on $A_{r1r2}(\nu, \tau)$, f_1, f_2 and α_1, α_2.

The two auto terms of the PWLFM contain a sinc function which is concentrated around the line $(\nu - \alpha\tau)$ in the ambiguity domain peaking at the origin and spreading out along the line away from the origin. The function is limited in the lag direction due to the $\mathrm{rect}(\tau, 2T)$ function and also decreases in amplitude away from the lag origin due the $(T - |\tau|)$ component. The modulation of this sinc function depends on the values of T, α and f. Regardless of this modulation the majority of the energy of this function is contained around the line $(\nu - \alpha\tau)$ and it is on this principal that we base the proposed ambiguity domain filter which windows along this line.

The cross terms on the other hand are spread across the ambiguity domain depending on values of $\pm(f_1 - f2)$, $(f_1 + f_2)$, $\pm(\alpha_1 - \alpha_2)$, $(\alpha_1 + \alpha_2)$, $A_{r1r2}(\nu, \tau)$ and $A_{r2r1}(\nu, \tau)$. These cross terms are an essential component of the signal needed to uniquely identify it in the ambiguity domain. Thus for the detection of a known signal using TF correlation if the ambiguity domain filter is equal to $\hat{A}_z(\nu, \tau)$ then a perfect correlation will be achieved. However for the case when the PWLFM is a mere approximation of some quasi-LFM signal then applying an ambiguity domain filter equal to $\hat{A}_z(\nu, \tau)$ will result in a filter shape containing the broad spread of the cross terms across the doppler-lag domain. It is proposed that the filter shape may pass through spurious components not associated with $A_z(\nu, \tau)$ to the TF test statistic $\eta_{TF}(t_0, f_0)$. Thus by applying an ambiguity domain filter based on the main components which are situated around $(\nu - \alpha\tau)$ results in a more robust correlation of some quasi-LFM signal embedded in noise.

The TF matched filter method proposed by Boashash and Mesbah [7] defines a template TFD to correlate with the EEG TFD to obtain the test statistic $\eta_{TF}(t_0, f_0)$. The template TFD for $z(t)$ can be constructed from the parameters $[T_1, T_2, \alpha_1, \alpha_2]$ where the order and values of these parameters uniquely defines the template. For the proposed method, using a Gaussian window to window around the lines $(\nu - \alpha_1\tau), (\nu - \alpha_2\tau)$, the ambiguity template can be defined (for the general case of a L piece PWLFM) signal as

$$A_{ref}(\nu, \tau) = \sum_{i=1}^{L} \mathrm{e}^{\frac{-(\nu - \alpha_i\tau)^2}{2\sigma^2}}$$

where σ^2 represents the variance of the Gaussian window and can be set accordingly. As this is time independent it is obvious that the template function defined by $[\alpha_1, \alpha_2]$ equals the template function defined by $[\alpha_2, \alpha_1]$ thus reducing the size of template set by half, assuming that $\alpha_1 \neq \alpha_2$. The parameters of $[T_1, T_2]$ are ignored to the determent of allowing other undesirable components (such as noise and possibly cross-terms) in the TF test statistic. However assuming that T_1, T_2 are large enough then the lag region of support is also large thus approximating the template.

3. RESULTS

In order to test the proposed method of seizure detection a model of newborn EEG seizure was initial used. This combines a nonlinear nonstationary seizure component with a nonlinear stationary background component plus additive WGN. The nonlinear stationary background component suggested by Celka and Colditz [8] uses a time series model (ARMA) followed by a nonlinear shaping component. The parameters for this background model were extracted from real newborn EEG data. To improve on this model the seizure model proposed by Stevenson *et al.* [9] will be included. This generates an amplitude varying PWLFM multicomponent TFD and obtains the time-domain signal through a TF signal synthesis algorithm.

This synthetic data was initially used to compare the TF matched filter with the proposed improved method and their ability to detect quasi-LFMs. The methods were compared with their ability to maximise the true detection rate (TDR) and minimise the false detection rate (FDR). The value of the TDR is determined by the ratio of the number of correct detections to the number of seizures and the FDR is the ratio of the number of incorrect detections to the number of non-seizure events. The TDR and FDR will be measured in terms of 20 second epochs which are classified as either seizure or non-seizure events.

For the TF matched filter PWLFM templates were constructed using the parameters $[T_1^i, T_2^i, \alpha_1^i, \alpha_2^i]$ for $i = 1, 2, \ldots, M$. The slope values α were assigned seven discrete values [-0.03, -0.02, -0.01, 0, 0.01, 0.02, 0.03] Hz/sec and the set was constructed for predefined (manually optimised) values of $[T_1^i = 5, T_2^i = 15]$ secs $\forall i$. The resulting template set contained $M = 42$ PWLFM templates. The proposed improved method, henceforth named the ambiguity filter method, used a reduced set of templates compared with the TF matched filter method as it only requires $M = 21$ to uniquely approximate the set of PWLFMs. A threshold value on the decision statistic was manually optimised for both methods separately. Smaller sets, namely $M = [10, 20]$ for the TF method and $M = [5, 10]$ for the ambiguity filter method, were also used to highlight the dependence of TF matched filter method on set size when compared with the ambiguity filter method's robustness (lower sensitivity to FDRs with increased set size) to template set size.

Ambiguity Filter Method			TF Matched Filter Method		
M	TDR	FDR	M	TDR	FDR
5	31:35	1:35	10	14:35	2:35
10	31:35	0:35	20	7:35	5:35
21	33:35	0:35	42	24:35	11:35

Table 1: The two methods tested with 12 minutes of simulated newborn EEG data sampled at 10Hz using 20 second epochs for different template set sizes M. For the seizure components the signal to background ratio was set to 5dB and the SNR was set at 0dB.

The TDR and FDR results for the simulated EEG data are displayed in Table. 1 where the reduced template set of the ambiguity filter method outperforms the TF matched filter method in producing both a higher TDR and lower FDR. This highlights the ability of the ambiguity filter method to filter only the auto terms of the quasi-LFM which results in a more robust method to detect quasi-LFMs that do not exactly match the template PWLFM. The TF matched filter on the other hand suffers from a higher FDR due to the large template set required to match the randomly generated seizure (which is created from a per epoch randomly varying three piece amplitude varying PWLFM signal). The TF correlation of the matched filter filters the epoch with the template in the ambiguity domain, thus allowing both the cross-terms and auto-terms through. When this correlation is not a perfect match the method allows more spurious energy into the correlated TFR thus resulting in a higher FDR.

Method	Set Size M	TDR	FDR
Ambiguity Filter	21	136:148	17:73
TF Matched Filter	42	146:148	70:73

Table 2: The two methods tested on real neonatal EEG data. The TDR was calculated on 25 minutes of seizure data that was added together from 3 different babies and the FDR rate was taken from a 12 minute recording from one baby. All EEG data consisted of 20 channels where each channel is analysed independently. M represents the template set size.

The two methods were then tested on real neonatal EEG recordings where seizure/non-seizure has been classified by the neurologist. The detection method consisted of analysing 20 channels separately on a per epoch basis, with an epoch length of 20secs moved along in time with a 50% overlap. To calculate the TDR and FDR each epoch was classified either seizure/non-seizure. Therefore an epoch is classified as a seizure if one or more seizures were detected in any of the 20 channels for that epoch. In terms of FDRs the ambiguity domain method again outperforms the TF matched filter method as displayed in Table. 2. The TDR rate of the TF matched filter is slightly greater than that of the ambiguity domain method but at the expense of a very high FDR. The ambiguity domain method may produce a more accurate detection of quasi-LFMs in EEG data as todate there is no evidence to state that these features are continually present in neonatal EEG seizures. Improved results would be expected if the both methods used a template set based on more than a 2 piece PWLFM signal.

4. CONCLUSION

A more robust method of neonatal EEG seizure detection using a TF matched filter for feature detection is presented. The proposed feature associated with seizure is a quasi-LFM signal whose exact characteristics have a large degree of patient variability. The TF matched filter method is highly dependent on the template set to produce accurate results as generally the larger the set the higher the FDR. The proposed method is more robust in terms of template selection while maintaining a low FDR. This method also has the advantage of reducing the size of the template set and excluding the need for actual correlation in the TF domain as this is carried out directly in the ambiguity domain. This results in reducing the computational complexity of the detection method.

5. REFERENCES

[1] W. A. Gardner, *Introduction to Random Processes with Applications to Signals and Systems*, McGraw-Hill, New York, 1989.

[2] P. Flandrin, "A time-frequency formulation of optimum detection," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 36, no. 9, pp. 1377–1384, Sept. 1988.

[3] B. Boashash, Ed., *Time-Frequency Signal Analysis and Processing : A Comprehensive Reference*, Elsevier, Oxford, UK, 2003.

[4] M. B. Shamsollahi, L. Senhadji, and R. Le Bouquin-Jeannes, "Detection and localization of complex SEEG patterns in epileptic seizures using time-frequency analysis," *Proc. IEEE-SP Int. Symp. Time-Frequency and Time-Scale Analysis*, pp. 105–108, June 18–21, 1996.

[5] L. Senhadji and F. Wendling, "Epileptic transient detection: wavelets and time-frequency approaches," *Clinical Neurophysiology*, vol. 32, pp. 175–192, 2002.

[6] S. J. Schiff, D. Colella, G. M. Jacyna, E. Hughes, J. W. Creekmore, A. Marshall, M. Bozek-Kuzmicki, G. Benke, W. D. Gaillard, J. Conry, and S. R. Weinstein, "Brain chirps: spectrographic signatures of epileptic seizures," *Clinical Neurophysiology*, vol. 111, pp. 953–958, 2000.

[7] B. Boashash and M. Mesbah, "Time-frequency methodology for newborn electroencephalographic seizure detection," in *Applications in Time-Frequency Signal Processing*, A. Papandreou-Suppappola, Ed., chapter 9, pp. 339–369. CRC Press, 2003.

[8] P. Celka and P. Colditz, "Nonlinear nonstationary wiener model of infant EEG seizures," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 6, pp. 556–564, 2002.

[9] N. Stevenson, L. Rankine, M. Mesbah, and B. Boashash, "Newborn EEG seizure simulation using time-frequency signal synthesis," *Proc. APRS Workshop on Digital Image Computing*, pp. 145–151, Feb. 2005.